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Adaptive Fuzzy Heuristic Algorithm for Dynamic Data Mining in IoT Integrated Big Data Environments

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Abstract

The explosion of Internet of Things (IoT) devices has created enormous amounts of real-time data, requiring sophisticated Data Mining Methods (DMT) that can rapidly extract valuable insights. Managing the computational complexity of processing high data volumes, integrating various IoT data formats, and ensuring that the system can scale are among the most significant issues. Fuzzy Dynamic Adaptive Classifier Optimization Analysis (FDACOA) is a method that has been suggested as an approach to the difficulties caused by changes in data patterns, processing in real-time, and data heterogeneity. By incorporating Adaptive Fuzzy Logic (AFL) and heuristic optimization, FDACOA enhances data classification accuracy and efficiency while simultaneously assuring that the algorithm can adapt to changes in data streams. This adaptability is crucial in IoT applications, where data fluctuation might affect analysis quality. FDACOA uses dynamic adaptation to alter classifier parameters based on real-time feedback to improve prediction accuracy and reduce computing costs. An optimization layer fine-tunes fuzzy rules and membership functions to optimize performance across data situations. Simulation analyses proved the algorithm's capacity to classify with high accuracy and low computational cost. Smart healthcare, predictive maintenance in industrial IoT, and intelligent transportation systems use FDACOA for real-time decision-making and data-driven insights. FDACOA is a viable approach for dynamic data mining in IoT-enabled big data contexts because of its faster, more accurate, and more adaptable simulation results.

Keywords: Fuzzy heuristic algorithm, Dynamic data mining, Internet of things, Integrated big data environment, Classification optimization.

1 | Introduction

In the context of large datasets and the IoT ecosystem, conventional techniques for dynamic data mining are finding it hard to manage complexity, scalability and flexibility [1]. This is more so when dealing with large, complex datasets with varying characteristics. The environments of IoT should continuously present fresh

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data, which k-means clustering, rule-based systems, and decision trees cannot address [2]. These techniques fail to refashion in changing environments as the data and its characteristics change. Efficiency and accuracy have suffered. The response time of such real-time data analysis techniques is often limited because of the high computational cost associated with such conventional methods [3].

In IoT applications, time is a critical factor in the decision-making process. Parameter adjustment by human operations due to the change of data attributes will result in the degeneration of the system's performance. The data from IoT is complex and hard to manage due to their high dimensions and diversity [4]. With their limitation, conventional means cannot manage and find such intricate data structures. In dynamic targeted applications and with large data volumes, such systems are not applicable since they can neither adapt nor learn [5]. Solving these issues requires more sophisticated approaches, such as adaptive fuzzy-based approaches. Such novel information structures can be embedded into these algorithms' rules [6]. For this reason, data mining due to IoT would be less reactive, offering more flexibility. As these methods counter the existing limitations, they also enhance the scalability and real-time analytics [7].

Dynamic data mining with the FDACOA in the context of big data and IoT faces some issues [8]. The scope of the underlying concern is the high computer load and complexity involved in enduring the data stew. IoT devices and end users of communication networks generate 10x, 100x and 1000x volumes, speed and diversity of real-time data, which also proves difficult for the FDACOA since adjusting and retaining the fuzzy rules is hard without losing accuracy [9]. Real-time changes may be costly in processing resources and may introduce delays in data changes as the changes will require the real-time rule to be adjusted to the changing data per the algorithm's requirements [10].

Telemetry data sent by IoT devices consists of many sensor readings, text, and other multimedia inputs, making it even more difficult to reach conclusions; thus, the modelling strategy of FDACOA has to be dynamic. Fuzzy systems provide interpretability. However, the adaptation process using FDACOA can lead to the development of complex rule sets, which results in an opaque decision-making process.

Another problem is balancing complexity and interpretability [11]. Initially, IoT data streams had many variables, such as noise and uncertainty. Problems are complicated without data sparsity and missing values; innovative preparation strategies are sometimes needed to maintain data quality [12]. These problems underscore the need to improve FDACOA to manage the diversity, scalability, and ambiguity of huge volumes of IoT data while maintaining low latency and strong interpretability in dynamic situations [13].

FDACOA fuzzy rules are adjusted in real-time to reflect changing data patterns. It handles dynamic data mining problems in large data and IoT situations [14]. Genetic algorithms and swarm intelligence may simplify computer jobs and speed up adaptation. When handling heterogeneous data, FDACOA uses a hybrid method [15]. The company may use fuzzy logic and Machine Learning (ML) algorithms to analyze data. In dynamic situations, robust data preparation solutions control noise and missing values to offer high-quality data and enhance decision-making [16].

A novel approach developed for big data environments that include the Internet of Things (IoT) is the Fuzzy Dynamic Adaptive Classifier Optimization Analysis (FDACOA), which is the focus of this research. In contrast to conventional approaches, FDACOA uses an adaptive fuzzy heuristic mechanism to tune classifiers in real-time, guaranteeing scalability and high accuracy even when data circumstances fluctuate. This mechanism is especially useful for dealing with dynamic and diverse IoT data. With its capacity to adapt on the go and its decreased processing cost, large-scale IoT datasets can be efficiently handled. Filling a crucial need in current IoT Data Mining Methods (DMT), the research brings a novel framework that improves classification accuracy while offering a scalable and resource-efficient solution that enhances state-of-the-art methods.

The main objective of the paper is:

I. Designing the FDACOA based on Heuristic optimization and Adaptive Fuzzy Logic (AFL) increases IoT data classification accuracy. The algorithm can thus handle real-time data streams' complexity and unpredictability.

II. The goal is to provide real-time feedback-driven dynamic parameter adjustment of classifiers, allowing the system to adapt to changing data streams while preserving high prediction accuracy in IoT applications prone to oscillations.

III. The optimization layer adapts fuzzy rules and membership functions to simplify processing vast amounts of different IoT data.

IV. The experimental results demonstrate that the proposed model increases computing efficiency, scalability, and accuracy, reducing latency compared to existing models.

The following is included in this section, which organizes the structure of the research paper. Section 2 of the paper delves into the adaptive fuzzy heuristic algorithm that is used for dynamic data mining in big data environments that are integrated with the IoT. Analysis of Fuzzy Dynamic Adaptive Classifiers (FDACOA) is the subject of Section 3 of this dissertation. A comprehensive analysis, comparison to prior approaches, and discussion of consequences are presented in Section 4. The results are thoroughly examined in Section 5.

2|Literature Review

The exponential expansion of IoT and big data analytics has spurred several novel techniques to optimize resource management, system performance, and decision-making.

Sunhare et al.'s [17] strategy improves decision-making, system performance, and resource management. This approach analyzes numerous DMT for IoT applications and a cloud-assisted large data mining system with only 78.2% efficiency. This method's outcomes are suggested enhancements.

Jiang et al. [18] and colleagues devised the approach, which increased accuracy, training time, AUC and G-mean metrics across datasets and reduced scalability by 88.3%. This may be achieved via a Fuzzy Rule-based Classifier (FR-C), incremental ensemble classification, and dynamic weighting.

Elaggoune et al. [19] established a multi-fuzzy agent-based wireless sensor network using Multi-Agent Technologies (M-AT) and fuzzy logic to provide high-quality data extraction, lower energy consumption, and a longer network lifetime. Two technologies were combined to achieve this. The given method achieves these goals.

Saha et al. [20] suggested these IoT uses. The recommended approach integrates meta-heuristics with Machine Learning Methods (MLT) to improve efficiency and provide smart solutions for smart cities, agriculture, and edge education.

Latchoumi et al. [21] introduced IoT sensors, computational approaches, and unique algorithms such as HWO, HMP, and HFC are utilized in the suggested method to strengthen mining safety and water quality, as well as improve sustainability and less in prediction latency with 87.1%.

Sundarakumar et al. [22] invented query optimization and clustering; the suggested method makes use of the Enhanced Salp Swarm Algorithm (ESSA) and the Modified K-Means (MKM) algorithm. This increases the speed at which data is processed while maintaining an accuracy rate of 70.6% in a big data environment.

Kousis and Tjortjis [23] invented to investigate the DMT utilized in smart cities; the proposed method employs Bibliometric Analysis (BA) in conjunction with the Bibliometrix library. This discovery reveals a wide range of methodologies and a quick expansion in this multidisciplinary research field, which has reduced resource utilization by 56.2%.

Fan [24] suggested the Home Automation with IoT. Wi-Fi, GSM, Bluetooth, and ZigBee are communication protocols that may link the design to user devices. Current systems use various monitoring sensors and structural components for effective energy management. Such applications have been used in many different

contexts before. Using these technologies, people can keep tabs on how much energy they consume from anywhere, which helps cut down on waste and is better for the environment. It is essential to keep digging for ways to save energy to lessen the blow of increasing energy demand.

Adeniran et al. [25] proposed the Cloud-Centric IoT Transformations. For AC Manufacturing Inc., a medium-sized auto parts manufacturer, cloud computing aims to increase income or decrease the time spent on different jobs. With cloud computing, the many divisions of the whole company might run together more smoothly. On the other hand, cloud computing raises several concerns that might become problematic in the future concerning legal accountability, credibility, security, and dependability. Consequently, after carefully weighing the pros and cons of cloud computing, it is recommended that AC Manufacturing Inc.'s management adopt this model while regularly educating and retraining employees.

Algarni [26] recommended the Wireless Sensors Network (WSN)-Based Detection of Wildfires. The oxygen that woods provide is vital, as is well known. Humans must take responsibility for preserving the planet's natural resources. Preventing forest fires is one of the many methods available. Quicker fire detection and prevention are possible with this method. Animals and trees both perish in forest fires. While methods such as human monitoring, satellite systems, and webcams may all identify forest fires, the Forest fire detection system can do so in a matter of seconds and set off alerts accordingly. In this method, the author can expedite rescuing trees and animals.

El-Morsy [27] discussed the involvement of WSN in today's world. WSNs include wireless communication, a thesaurus, and the ability to measure physical signals; they also provide rapid connectivity in several parts of the economy, including healthcare, environmental monitoring, industry, and agriculture. WSN can monitor and locate home equipment as an automated device control. As such, it serves as an inquiry into the many kinds and uses of wireless sensors in the house and outside. Sort research on WSN applications is described in this report.

Chang et al. [28] deliberated the artificial intelligence management model for water resource recovery and purification system. This conceptual paper suggests developing and executing a wastewater treatment system to improve efficiency and decrease operating costs. Its goal is to accomplish intelligent wastewater treatment management by emphasizing proactive measures to guarantee steady operation and directing the sector towards more efficient and environmentally friendly practices.

Saraswathi et al. [29] presented the combined disjoint block fuzzy cognitive maps for the decision mathematical approach. This method is useful in many domains with a lot of uncertainty or partial data since it can handle linear and nonlinear programming. Fuzzy optimization provides strong, flexible approaches to theoretical and practical optimization, making it an indispensable tool for tackling complicated, uncertain situations in the real world. A mixed disjoint block fuzzy cognitive map was used in a separate study to examine transgender problems in Tamil Nadu from a mathematical perspective.

Saadati et al. [30] suggested that the ticket response process in customer support systems should use ML. This research prioritizes support system concerns by prioritizing support system concerns by utilizing ML methods, particularly Natural Language Processing (NLP) and Tag Cloud Representation. Password and username retrieval difficulties accounted for most typical problems, according to the study that used data gathered from individual and business organizations over one month. This study highlights the significance of ongoing planning and incorporating more ML algorithms to improve IT systems' support processes and progress digitalization.

Cai et al. [31] investigated the Dynamic Adaptive Multi-Objective Optimization Algorithm Based on Type Detection (TDA-DMOEA). The primary goal in developing the dynamic detection operator was to catalog the many forms dynamic issues may take. The Wilcoxon signed-rank test and Hyper Volume (HV) identify POS and POF differences in nearby contexts. Distinct reaction mechanisms are developed to deal with various DMOP alterations. Specifically, a closed-kernel-function Multi-Angle-Based Transfer Learning Approach (MA-TL) is established when both POS and POF undergo modifications simultaneously.

Sun et al. [32] examined the Adaptive Fuzzy Neighborhood-Based Multilabel Feature Selection (AMFSA) with Ant Colony Optimization (ACO). The feature space and label space are used to generate the feature cosine similarity and the label Jaccard similarity between samples. A dynamic adjustment coefficient is created to regulate the significance of label similarity, and by integrating the two similarities discussed earlier, we suggest that total sample similarity should accurately represent total space similarity. A discriminant relation is suggested to determine whether the link between samples is homogenous or heterogeneous. The second issue is that the fuzzy neighborhood radius is sometimes picked arbitrarily; to fix this, the author averages the distances between the target sample and all the other samples, whether homogeneous or heterogeneous.

Chithaluru et al. [33] introduced the energy-balanced neuro-fuzzy dynamic clustering scheme for green and sustainable IoT-based smart cities. The suggested method for creating network clusters is based on a self-organizing neural network. The test-bed analysis is conducted to compute the TinyOS sensor nodes for real-time event detection and clustering. Compared to other popular green communication routing protocols, such as Low-energy Adaptive Clustering Hierarchy (LEACH) and Low-energy Adaptive Clustering Hierarchy-Centralized (LEACH-C), the suggested protocol performed far better in the simulation. The outcomes of the suggested model demonstrate that neuro-fuzzy logic is useful for green smart city applications and sustainable IoT devices when managing resources and dynamically grouping data. In comparison to LEACH and LEACH-C, the suggested protocol exhibits a 35% improvement in average metrics such as First Node Dies (FND), Last Node Dies (LND), packets transmitted to CH and BS, network convergence time, network overhead, and average packet latency.

Safa et al. [34] suggested the social media-based mental health prediction. The author describes common methods for predicting and detecting the disease via user-generated material. Methods for gathering data, extracting features, and making predictions form the backbone of this study's structure. In addition, the author discusses the analytical methodologies and aspects of candidate profiles by reviewing other recent research. After that, the author explores current and future developments in experimental auto-detection frameworks for detecting people with diseases, and we get into several debates surrounding these frameworks.

Muniz and Muniz [35] recommended the IoT-Integrated Smart Homes. Using an IoT architecture as a starting point, this article delves into the challenges encountered by smart home systems that are IoT-enabled and offers suggestions for overcoming them. A smart house streamlines the home automation process and provides consumers with more convenience. After the success of the Industrial WSN with the IoT, it is only natural to see IoT used in smart homes. The paper delves into several facets of smart homes that rely on the IoT and stresses the need for solid management and security measures. The research concludes by looking at smart house IoT integration, illuminating the problems and solutions linked to smart home IoT system development.

Wanke et al. [36] introduced the performance evaluation and lockdown decisions of the UK healthcare system. The first step is to use Complex Proportional Assessment (COPRAS) or Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to calculate partial utility functions or partial distances, respectively. Secondly, the Latent Vagueness and Randomness Components (LAVRA) approach removes uncertain components from unbiased performance ratings. Third, drivers of lockdowns are categorized using performance, fatalities, and areas employing a bootstrapped neural network regression.

Bagherzadeh Asl [37] discussed that the WSN assists the rancher with creating a high harvest and diminishing the expense of yield. Climate change, ecological shifts, and catastrophic events affect agribusiness. With WSN, CEOs should be able to access both water and dirt. It will require much work in the agricultural sector to overcome this WSN. Horticulture uses WSN for various tasks, including monitoring and calculating temperature, water system design, supply, etc. Because remote sensors are used here, the execution cost is quite inexpensive.

Yu [38] examined the integration of WSN and IoT for Crop Growth Monitoring. This study delves into the many important problems and issues of smart agriculture as it pertains to the IoT. Wireless networks and

associated terms are also defined and discussed in the study. This article looks at the recent developments in smart agriculture, the IoT, and wireless networks, and it highlights several potential avenues for further study that might add to the system's operational, economic, and technological polish.

Najafi et al. [39] suggested the Artificial Intelligence of Things (AIoT) and Industry 4.0–Based Supply Chain (FMCG Industry). Given the supply chain's central role in manufacturing, particularly the Fast-Moving Consumer Goods (FMCG) industry, which touches people's lives daily, this chapter lays out a plan for using this technology at that stage. Using this structure, the many messages these developing technologies send throughout the supply chain will have a defined course.

Najafi et al. [40] recommended the key parameters affecting sustainable IoT-based marketing. A company may achieve its sustained competitive edge with the use of the IoT and the possibilities it offers to management. Researchers have found that the following factors are important for successful IoT smart marketing: perceived utility, convenience of use, trust, social acceptability, pleasure of usage, and controllability. The author analyzed and prioritized these crucial indicators. Lastly, a structure is provided to articulate the viewpoints on how the IoT affects environmentally conscious advertising.

Torabi [41] presented the Greenhouse Monitoring with WSN. To remotely regulate the borders of the greenhouse, this study suggests a WSN-based implanted framework and oversees the execution of the ZigBee organization (via IEEE 802.15.4). The greenhouse displays detailed information about the ZigBee network's basis in star geography and Mesh Topology. A PC-based GUI application developed on the Java platform also displays the constant monitoring of parameters such as temperature, humidity, and the system's overall power consumption.

FDACOA outperforms other dynamic DMT because of its flexibility and performance. Its capacity to handle drifting ideas and real-time data streams has made it a leading solution in big data analytics and the IoT.

3 | Proposed Method

People use devices that belong to the IoT; as expected, a lot of data that needs to be worked upon in real time is created. However, they would still be of no use without containing usable data. Working with such large quantities of information is difficult, especially when such information is heterogeneous. This paper introduces the Fuzzy Dynamic Adaptive Classifier Optimisation Analysis (FDACOA). FDACOA, in terms of IoT data, can keep up with the changing patterns and requirements of information processing, more so in real time. FDACOA's systems can utilize perceptual heuristic optimization and AFL to fit different data. Smart health care and predictive maintenance in industries that are aspects of the IoT are examples of those who crave fast and accurate results.

FDACOA is one step forward since it provides real-world usability in continuous and timely decision-making in unsupervised data mining concerning IoT. A continuous review of classification accuracy and error rates may reveal concept drift, defined as data distribution changes over time. In response to detected drift, the framework re-optimizes the classifiers in real time by adjusting the decision bounds and recalibrating the fuzzy rules to account for the changed patterns in the data. The model can handle the non-stationary nature of IoT data streams efficiently and resiliently because of this iterative adaptation, which keeps it sensitive to developing patterns without requiring thorough retraining.

Designing the FDACOA framework

The issues with IoT data that FDACOA aims to solve are handling varied formats, adjusting to data oscillations, and ensuring real-time processing. Heuristic optimization improves speed invisibly, while AFL allows FDACOA to adapt to changes in data patterns automatically. Another interesting feature is that the approach may dynamically change classifiers; thus, it can adapt its performance to real-time input. Statistical gathering is not enough for FDACOA. It receives and processes fresh data, improving its performance and accuracy.

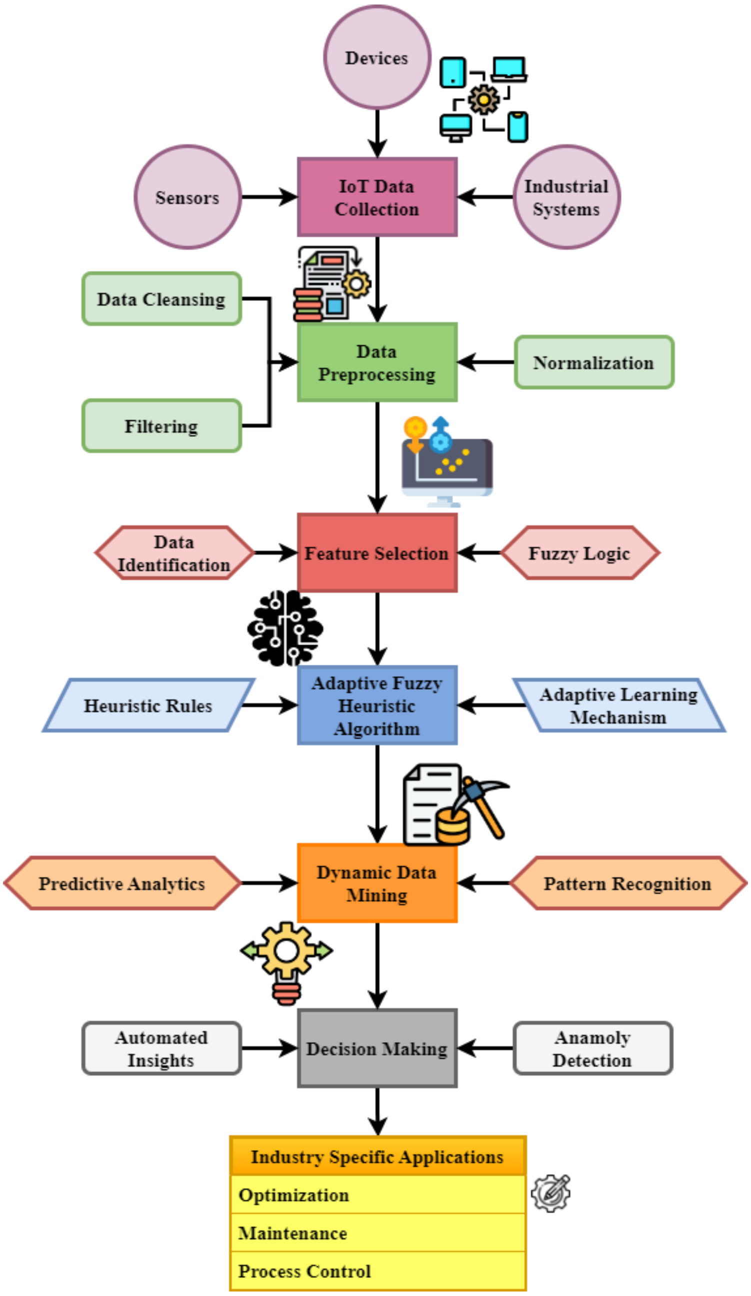


Fig. 1. Framework of FDACOA for real-time dynamic data mining in IoT systems.

Fig. 1 shows the FDACOA method to dynamically mine data from IoT devices. It shows the different steps, beginning with gathering data from industrial systems, sensors, and devices via the IoT. Data is prepared for analysis by cleaning, filtering, normalizing, and selecting features. Important data aspects are identified using fuzzy logic and heuristic methods. FDACOA is an online classifier that continuously improves classification performance as new data is fed. It does this by incorporating an adaptive fuzzy heuristic algorithm. As this is a data mining technique, it makes decisions based on available data and performs trend analysis in real-time and forecasts. This method favors processes that need improvement, performance upkeep and control. The structure is necessary for IoT applications like smart transport systems, better healthcare, and industrial predictive maintenance due to its low processing costs and high classification performance with learning adaptability.

$$-\gamma P' = \delta_{\varepsilon-2} V(\partial + \text{For all}' Qw) - \sigma'(\pi' - rt). \tag{1}$$

Eq. (1) depicts the dynamic adjustment of classifier parameters (∂) in reaction to patterns in real-time data (Qw), using heuristic optimizations and fuzzy membership functions. *Eq. (1)* shows the dynamic feedback loop allows fuzzy rules to be fine-tuned incrementally, enhancing prediction accuracy while maintaining low computational cost. This approach enables the classifier to efficiently adapt to changing data distributions in real-time, making it highly effective for resource-constrained IoT environments. Fuzzy rules may be fine-tuned to improve forecast accuracy with little processing cost by using adjustment coefficients $\delta_{\varepsilon-2}V$ and $-\gamma P'$ that are dependent on feedback ($\sigma'(\pi' - rt)$) and data variance.

$$p|\partial R' - uz| = \varepsilon_{b-gt}^{2} < My - kp(\Delta - r'') >. \quad (2)$$

Eq. (2) shows the connection between changes in real-time data ($p|\partial R' - uz|$) and adjustments made by adaptive classifiers (ε_{b-gt}^{2}). The equation $My - kp$ demonstrates how the data difference is dynamically weighted, and $\Delta - r''$represent the membership functions are optimized according to changes in streams of data.

$$|Mt - y; e - q''| = F(M - vc'') + \beta d. \quad (3)$$

The *Eq. (3)* that depicts the discrepancy ($Mt - y$) between the expected outcomes ($e - q''$) and the actual outcomes (F) in live IoT data settings. The term represents the adaptive fuzzy optimization process ($M - vc''$) and involves fuzzy rules that adapt to changes in real-time data (βd). *Eq. (3)* enables FDACOA to maintain high accuracy and efficiency across diverse IoT data streams, effectively addressing challenges related to dynamic data distributions and heterogeneity.

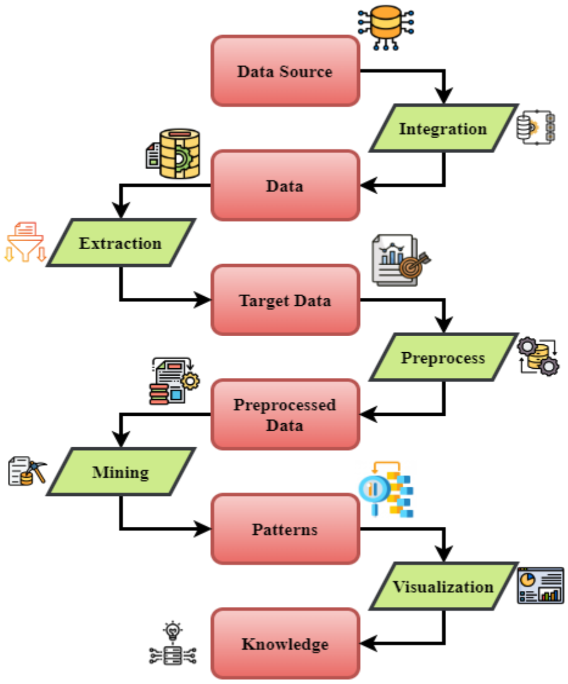


Fig. 2. Data mining workflow in FDACOA for IoT data processing.

In *Fig. 2*, we can see the flow of data processing within the FDACOA framework, emphasizing data from the IoT. Data extraction to construct the target dataset follows the integration of many IoT data sources. Preprocessing methods help ensure the target data is suitable for mining, cleaned, and structured. During the process of data mining, insights are displayed through the use of visualizations that are produced from meaningful patterns that were collected. It is possible to get insights from patterns that assist in making decisions in the here-and-now situations.

This method improves the FDACOA strategy by making it easier to handle large amounts of heterogeneous data at every level, from integrating data sources to extracting useful information. Each step is necessary to

solve the problems caused by IoT data. A scalable system, one that can analyze data in real-time and learn and adapt, are all necessary components.

$$\text{Tan D}\big(\text{F}' - \text{et}(\text{Mt} - \text{y}'\text{r})\big) = |\text{Evf}(\text{Mp} - \text{ew}'')|. \quad (4)$$

The dynamic reaction describes the relationship between FDACOA and the *Eq. (4)* $(\text{F}' - \text{et})$ to differences between actual results and real-time forecasts (TanD). The term $\text{Mt} - \text{y}'\text{r}$ represents the change in classifier parameters Evf due to fuzzy logic's reaction to changing data patterns $(\text{Mp} - \text{ew}'')$.

$$< \text{B}(\text{D} - \text{re}'') > \text{Nj}(\text{E} - \text{kv}'') * \text{EmT}(\text{Y} - \text{a}''). \quad (5)$$

The FDACOA technique is related to *Eq. (5)* because it uses fuzzy logic to express the interplay B between data input deviations $(\text{D} - \text{re}'')$ and classifier optimization $(\text{Nj}(\text{E} - \text{kv}'')$. Classifier rules are fine-tuned in real-time based on changes in the data to enhance the output accuracy (EmT), as described by the term $\text{Y} - \text{a}''$.

Real-time integration of FDACOA

The FDACOA implementation used fuzzy logic and a dynamic adaptation method to allow the real-time change of classifier parameters. Nothing about this was plug-and-play. Precise calibration was necessary to keep the approach efficient and responsive to new data inputs. The optimization layer of FDACOA continuously improves the method's performance by refining membership functions and fuzzy rules in real time, allowing it to adapt to new data circumstances. Its real-time categorization implementation has put it through its paces in several IoT applications, including smart healthcare and industrial IoT. These settings impact important decision-making scenarios with their quick and data-driven insights.

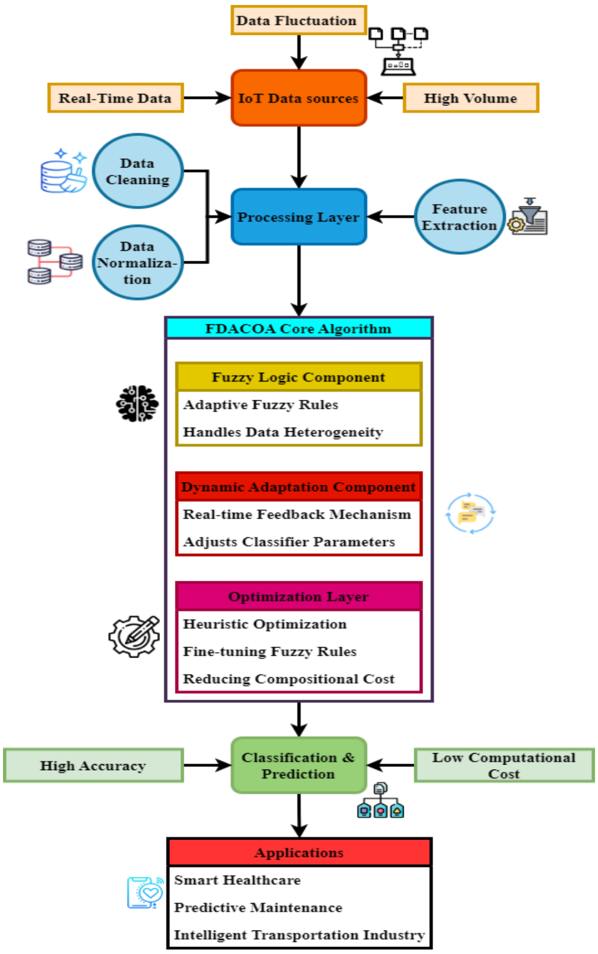


Fig. 3. FDACOA framework for adaptive IoT data classification.

Processing large amounts of real-time IoT data while adjusting to data fluctuations is the goal of the FDACOA architecture, as shown in *Fig. 3*. A data cleaning, normalization, and feature extraction layer processes the notoriously large and diverse amounts of data collected by the IoT. The FDACOA method has three primary components: the optimisation layer, the fuzzy logic component, and the dynamic adaptation component, which uses the preprocessed data.

The fuzzy logic component emerges into action whenever it is required to deal with data that is either flawed or confusing. It is the responsibility of the dynamic adaptation component to make consistent adjustments to the classifier's parameters to accommodate dynamic data patterns. The optimisation layer aims to achieve optimum speed while minimizing the amount of processing overhead by improving the fuzzy rules and membership functions.

This method has excellent classification and forecasting accuracy and low processing needs. Businesses in the smart healthcare, predictive maintenance, and intelligent transportation systems sectors may benefit from its IoT capabilities.

$$\delta(\mathrm{Ev}' - \mathrm{rt}) \colon \mathrm{Mv}(\mathrm{B} - \mathrm{sv}'') * \mathrm{Es}(\mathrm{v} - \mathrm{tp}''). \tag{6}$$

Eq. (6) illustrates how the FDACOA technique takes real-time circumstances into account while adjusting the classifier parameters ($\mathrm{Mv}(\mathrm{B} - \mathrm{sv}'')$) and evolving data streams ($\mathrm{Es}(\mathrm{v} - \mathrm{tp}'')$). The optimization of fuzzy rules to minimize mistakes in categorization is captured by the phrase $\delta(\mathrm{Ev}' - \mathrm{rt})$.

$$\mathrm{Uk} < \mathrm{N}' - \mathrm{bf} \geq \mathrm{T} < \mathrm{Mr}' - \mathrm{ut}(\partial + \mathrm{Rt}'') >. \tag{7}$$

The FDACOA technique is referenced by *Eq. (7)*, which describes how the classifier parameters ($\mathrm{T} < \mathrm{Mr}'$) are adjusted depending on thresholds ($\mathrm{Uk} < \mathrm{N}' - \mathrm{bf}$) in reaction to changes in real-time data patterns ($\mathrm{ut}(\partial + \mathrm{Rt}'')$).

$$[\mathrm{Mt}, \mathrm{ve} - \mathrm{N}''] = \mathrm{Y} < \mathrm{Ux} - \mathrm{pt}'' > + \mathrm{Ez}''. \tag{8}$$

The FDACOA technique is related to equation 8 because it shows how adaptive fuzzy adjustments ($\mathrm{Mt}, \mathrm{ve} - \mathrm{N}''$) affect the model output ($\mathrm{Y} < \mathrm{Ux} - \mathrm{pt}'' >$) and classification error Ez'').

For IoT-enabled settings, *Fig. 4* shows the predictive maintenance architecture used by the FDACOA technique, which targets data collected from machines and the surrounding environment via IoT sensors. The Data Acquisition Layer receives continuous and real-time data streams from many sources, including machines, sensors, and the environment. This layer cleans, normalizes, and detects outliers in the raw data before performing feature extraction.

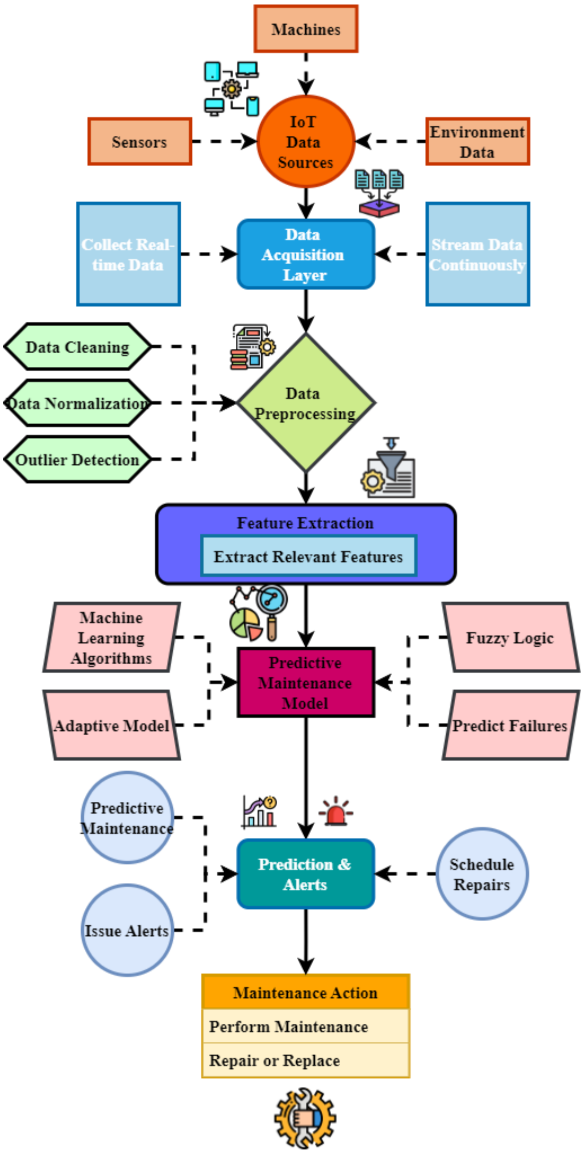


Fig. 4. Process flow of predictive maintenance model.

After identifying important characteristics, they are sent into the Predictive Maintenance Model that uses fuzzy logic and ML to foretell when machinery could break down. The improved accuracy of FDACOA's projections is attributed to its adaptive model. It can react to shifting data patterns. The system generates forecasts and alerts for users of possible issues, allowing for coordinated maintenance in real-time. Companies plan repairs and replacements according to projections to minimize system downtime. This method enables data-driven maintenance in smart and industrial settings enabled by the IoT.

$$Z_1(M - vf'') = R < n' - bf(\partial + 2v'') >. \tag{9}$$

The FDACOA technique is shown by the *Eq. 9*, which demonstrates how the classifier output ($Z_1(M - vf'')$) changes in response to real-time data fluctuations (R) and dynamic fuzzy logic optimization ($n' - bf$). The conditional and real-time feedback is denoted by the expression $\partial + 2v''$.

$$-E_w(R - u'q) = \text{For all}_2[\delta + tw'(\ni +St)]. \tag{10}$$

Eq. (10) is related to the FDACOA technique because it shows how the classification error (For all_2) may be reduced by adaptively adjusting the parameters ($-E_w(R - u'q)$) according to feedback ($\delta + tw'$) and patterns in real-time data ($\ni +St$).

Performance evaluation of FDACOA using optimization equation

Computation attention and classification accuracy-focused FDACOA simulations were deployed to evaluate these aspects. The optimization of the fuzzy rules and membership functions is aspired to improve the performance of the method as a measure. There has been a great achievement in various FDACOA IoT applications by reducing functional and performance distortion on sizeable binary classes. The testing showed that the system consumes the least resources while predicting the highest number of correct outputs with FDACOA by controlling various parameters due to the nature of the data. Up against all other solutions, F-DACOA appeals to the top place because of its efficiency and versatility, whereas data patterns in IoT scenarios are erratic.

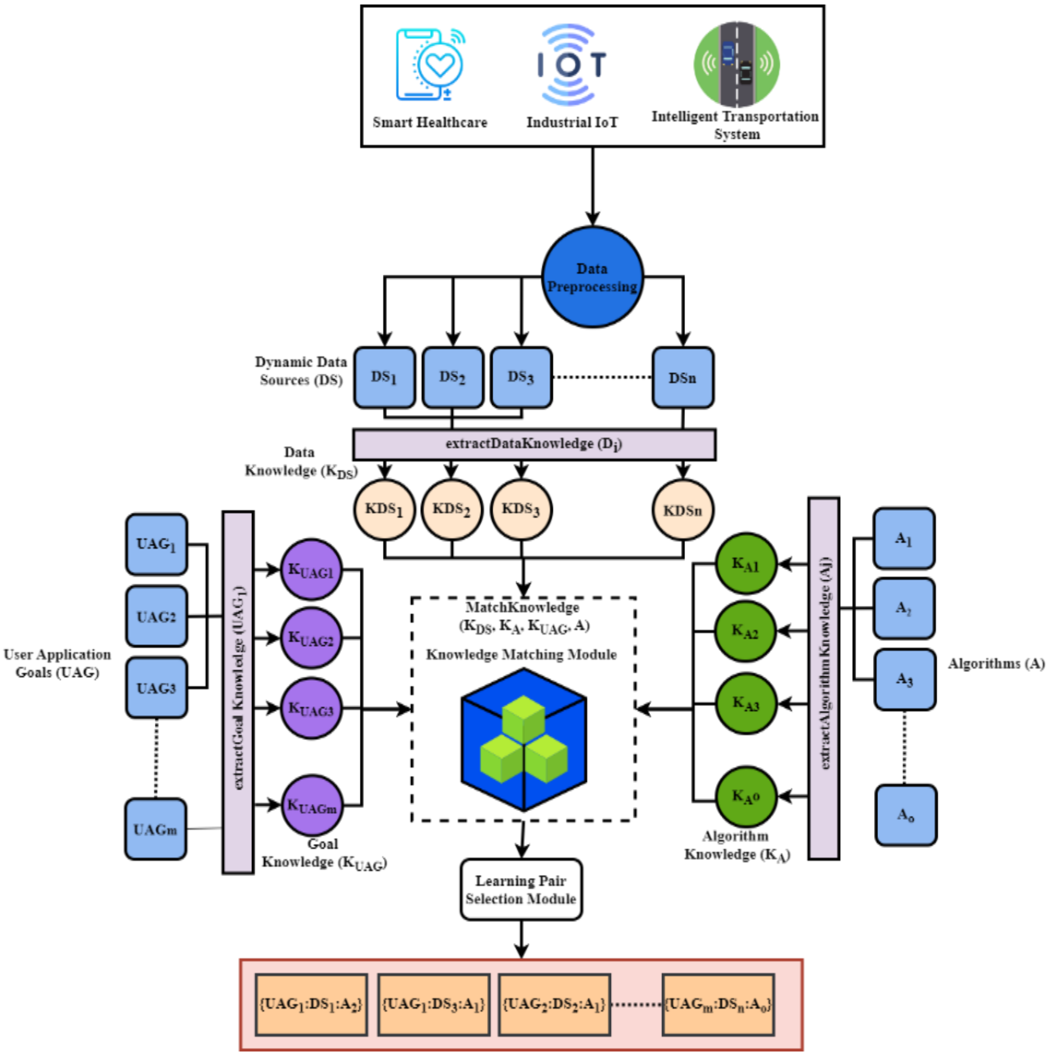


Fig. 5. Learning pair selection in FDACOA for IoT knowledge extraction.

Fig. 5 shows the FDACOA framework's learning pair selection module, which is responsible for extracting and pairing information for categorization in IoT applications. Several IoT Data Sources (DS_1 to DSn) are cleaned and normalized by preprocessing. Extracted Data Knowledge (D_i) is grouped into Knowledge Data Sets (KDS_1 to KDSn), which are further processed.

User Algorithmic Groups (UAG_1 to UAGm) contribute extracted user knowledge, while on the right, algorithm knowledge (A_1 to An) is derived from past learning experiences. The learning pair selection Module uses these two sources of information to create Knowledge Sets ($K^{UAG}{}_1$, $K^{UAG}{}_2$, etc.).

The fundamental FDACOA algorithm is given the learning pairs {UAG1:DS1:A1}, {UAG2:DS2:A2}, to perform dynamic classification and prediction. Smart healthcare, industrial IoT, and other applications may benefit from this method's improved prediction accuracy due to strong knowledge-sharing across datasets.

$$|V(Z', Typ'')| = \left(11 - st(v' - typ)\right). \tag{11}$$

A connection to the FDACOA approach is shown by *Eq. (11)*, which shows the link between the classification output variability ($V(Z', Typ'')$) and the adjustment based on inconsistencies between anticipated and actual values ($st(v' - typ)$). The phrase $v' - typ$ signifiesthefirst standard for classification accuracy.

$$\cup_e^r [M + n''] = V\left(Q - pt(Z - r'')\right). \tag{12}$$

The FDACOA approach is related to *Eq. (12)* because it shows how the variance of real-time data affects $Q - pt$ the collective adjustment of classifier parameters ($[M + n''] =$). In this case, the optimization function improves classification accuracy by integrating input from prediction differences $\cup_e^r$ is denoted by $V\left((Z - r'')\right)$. This highlights FDACOA's capacity to dynamically alter its fuzzy rules in response to changing data input.

$$\partial_2 V < Tr - mpk'' \geq \partial t''(v - cd''). \tag{13}$$

The assessment of predicted values $Tr - mpk''$ and real-time modifications affect the *Eq. (13)* capacity for classification ($\partial_2 V$). This dynamic feedback loop is crucial for observance classification accuracy high $v - cd''$, and the expression $\partial t''$ represents the model adjusts when there are differences between the actual and predicted output.

$$Z_1\text{"}Mtp(m - n'')\text{"}W(\partial \text{For all} - pt''). \tag{14}$$

The FDACOA method is connected to *Eq. (14)* because it displays how the weighted modifications of classifier variables ($Mtp(m - n'')$) affect classification outputs (Z_1). To modify the behavior of the classifiers, the $W(\partial \text{For all} - pt'')$ is very significant.

$$\delta < \gamma(\nabla + eT'') > mN\left(bV - ST(M - NB'')\right). \tag{15}$$

The FDACOA technique is supported by *Eq. (15*), which shows how the adaptive adjustment factor ($\delta < \gamma(\nabla + eT'')$) and the combined gradient effects mN work together to improve the performance $M - NB''$ of the classifier. The optimization process is denoted by the term $bV - ST$, where the variances between the expected and actual outputs are measured.

$$B_z\left(M - nb\left(Nt(Y - rt'')\right)\right) = B, n, Z(m - vb''). \tag{16}$$

As shown in *Eq. (16)*, in response to disparities in real-time data B, n, Z, the classifier parameters are adjusted ($M - nb$) in a way that affects $(m - vb'')$ the output classification variable (B_z). The technique's capability is reflected by the $Nt(Y - rt'')$ which specifies the interaction between numerous fuzzy logic variables.

$$B(Z' - rtp) = G(H\text{For all} + \omega'') - \alpha\beta''(D - fz''). \tag{17}$$

Integration of adaptive parameters ($B(Z' - rtp)$) affects the correlations ($\alpha\beta''$). In this case, the *Eq. (17)* $G(H\text{For all} + \omega'')$ the changes that were made to the model to account for gaps between the expected and observed values. This exemplifies FDACOA's capability to increase its classification processes and fuzzy logic rules continuously.

$$Vf(M - nbf'') = Jt\,(\partial - Vrt) + Rt(M - nb). \tag{18}$$

Fuzzy classification output $Vf(M - nbf'')$ is modified according to real-time feedback and data inconsistencies for *Eq. (18)*. The contribution of the dynamic modifications executed to raise classification accuracy $(\partial - Vrt)$ is indicated by the term Jt, and stabilization factors that assure consistent performance are demonstrated by $Rt(M - nb)$.

$$\mathrm{B(Zp - Ytr'') = Nz(\partial - Rt) - Z < N - bv'' >.} \tag{19}$$

The FDACOA approach is related to *Eq. (19)* since it shows how optimization of fuzzy rules and real-time modifications affect the classification output ($\mathrm{B(Zp - Ytr'')}$). The term $\mathrm{Nz(\partial - Rt)}$ symbolizes the feedback process that improves classification accuracy by considering outliers from anticipated results, while $\mathrm{Z < N - bv'' >}$ represents the changes implemented to accommodate for data input variability.

$$\mathrm{Y \to G(Tr - z; v') + Et(w - Xz'') * Rz.} \tag{20}$$

Here is *Eq. (20)*, which shows the output variable Y is obtained by combining adaptive parameters with real-time data. Equation ($\mathrm{G(Tr - z; v')}$) captures the effect of further adjustments based on the disparities in IoT data streams, while the fuzzy logic function $\mathrm{Et(w - Xz'')}$ handles the difference between goal and actual values. The capability of FDACOA to adjust its classification approaches on the fly is shown here.

$$\mathrm{B(v - w') = Mn(\partial + Re') - Tr(For\ all - q'').} \tag{21}$$

The AFL components' contribution to optimizing classification accuracy is reflected in *Eq. (21)* $\mathrm{Mn(\partial + Re')}$, while the adjustments performed to correct for inconsistencies in the anticipated $\mathrm{Tr(For\ all - q'')}$ versus actual outcomes are shown by $\mathrm{B(v - w')}$.

$$\mathrm{Bz(M - vc') + R(W - er' + Nt'') = 2w\ (For\ all + 2q'').} \tag{22}$$

Adaptive alterations to the classifier parameters impact the classification result, as shown by the *Eq. (22)*, $\mathrm{Bz(M - vc')}$. To increase predictions, the components such $\mathrm{R(W - er' + Nt'')}$, which highlights the integration of dissimilar inputs. The entire influence of the feedback loop and fuzzy logic modifications is exposed by $\mathrm{2w(For\ all + 2q'')}$, which highlights FDACOA's skill to enhance classification accuracy.

$$\mathrm{B\big(v' - wqb(M + nb)\big) = Em(\partial V' - wq).} \tag{23}$$

The connection between the FDACOA approach and *Eq. (23)* is shown by the way the interactions $\mathrm{\partial V' - wq}$ between the fuzzy parameters Em impact the classification output $\mathrm{B\big(v' - wqb(M + nb)\big)}$. This demonstrates that FDACOA can modify and improve its categorization method.

$$\mathrm{C(v' - wr'') = Tv(Eq' - wrt'').} \tag{24}$$

By showing the interaction between fuzzy logic parameters, Tv determines the classification output $\mathrm{C(v' - wr'')}$, the *Eq. (24)* coincides with the FDACOA approach. The adjustments were made due to input data inconsistencies captured by the $\mathrm{Eq' - wrt''}$.

$$\mathrm{\left(Y_q\right)(w' - Et) = |B < Zy(xt' - pw'') >|.} \tag{25}$$

The *Eq. (25)*, where $\mathrm{Y_q}$ is the difference between adaptive variables and real-time feedback affects the correlation coefficients. This connection shows how FDACOA improves forecast accuracy. To respond to the IoT data stream changes, FDACOA uses many feedback mechanisms.

The IoT data challenge is a real-time resolution of complex systems with highly dynamic datasets. The FDACOA method is new for addressing this problem. In FDACOA, due to optimization and AFL, classifier parameters can be modified in real-time to respond to the data-changing dynamics while maintaining low operational costs and high accuracy. The optimization layer of the approach enhances efficiency in varying data situations by refining fuzzy sets of membership functions and rules. The findings indicate that FDACOA applies new datasets easily to make accurate classifications. Applications in these sectors could include smart health, smart transport, and smart predictive maintenance of IoT devices. This proves its versatility in solving problems related to dynamic situation assessment. FDACOA presents a strong and flexible paradigm for advanced data mining. It fosters effective and fast manipulation of a large-scale microscope of an array of IoT data, thus making it a great application tool in large data climates.

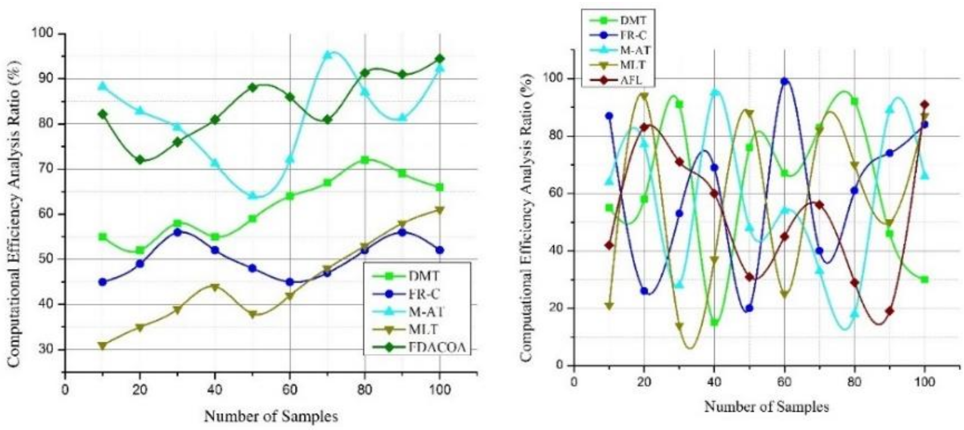
4 | Result and Discussion

The FDACOA performs its data mining processes in the context of big data and IoT applications, which are discussed in detail toward the end of this section. Some of the dimensions on which FDACOA and AFL are contrasted are efficiency, accuracy, scalability, prediction delay, and resource consumption.

Dataset description: For ML-based IoT and IIoT intrusion detection, the Edge-IIoTset Cyber Security Dataset is comprehensive and realistic. It uses seven levels of blockchain, edge computing, and cloud computing [42]. We replicate real-world events using data from over 10 IoT devices, including temperature, humidity, and heart rate sensors. DoS/DDoS, information gathering, man-in-the-middle, injection, and malware assaults are among the 14 attack categories in the dataset. It helps evaluate cybersecurity solutions in current IoT and IIoT contexts by supporting centralized and federated learning models in *Table 1*.

Table 1. Simulation environment.

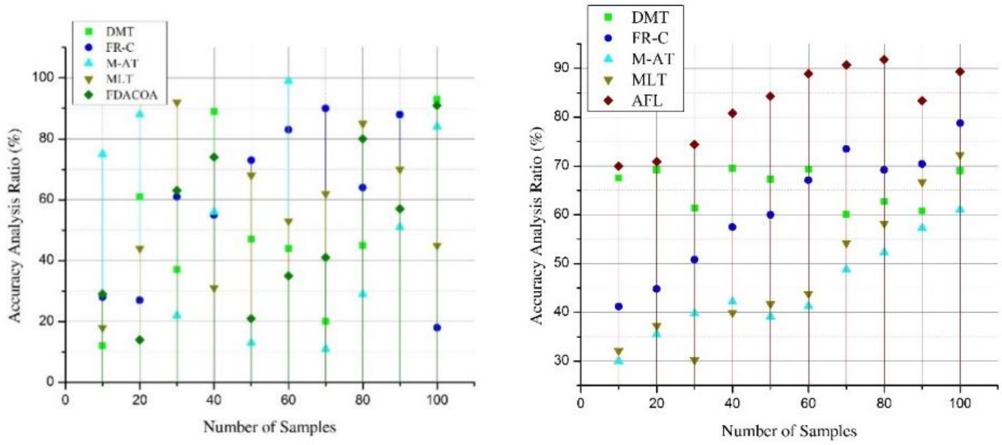
Layer	Technology/Platform	Description
Cloud computing layer	Cloud infrastructure (e.g., AWS, Azure)	Provides scalable and flexible cloud computing resources for storing and processing large datasets.
Network functions virtualization (NFV) layer	OPNFV platform	Virtualizes network functions, enabling the deployment of network services over a virtualized environment.
Blockchain network layer	HyperledgerSawtooth	Ensures secure and transparent transactions between IoT and IIoT devices, enhancing trust in data integrity.
Fog computing layer	Digital twin	Creates virtual replicas of physical devices to simulate and monitor the performance of IoT and IIoT systems.
Software-defined networking (SDN) layer	ONOS SDN controller	Manages network resources and dynamically controls traffic flow between devices, ensuring efficient operations.
Edge computing layer	Mosquitto MQTT brokers	Facilitates real-time communication between IoT devices and edge systems for low-latency processing.
IoT and IIoT perception layer	IoT Devices (Temperature, humidity, pH, soil moisture, ultrasonic, heart rate sensors, etc.)	Collects data from more than 10 types of sensors, simulating real-world IoT and IIoT applications.



a. b.

Fig. 6. Computational efficiency analysis is compared; a. FDACOA, b. AFL.

In *Fig. 6*, real-time processing and decision-making require computation-efficient dynamic data mining in big data and IoT scenarios. Swarm intelligence and genetic algorithms are AFL heuristic optimization methodologies. These methods simplify membership function and fuzzy rule adaption, reducing data processing time. This optimizer adjusts parameters based on incoming data patterns to minimize computing overhead. This ensures the algorithm's continued efficacy irrespective of the state of the data streams. FDACOA uses parallel processing to manage massive IoT data flows. Insight extraction from complicated, multi-dimensional data is faster when FDACOA parallelizes data processing. AFL applications boost computing performance by prioritizing valid data segments and reducing needless calculations. Intelligent transportation and predictive maintenance use enormous data sets with a range of information to process quickly using *Eq. (21)*. FDACOA suits these jobs because it balances real-time flexibility, and computational economy produces 94.5%. Due to this, AFL can maintain a low computing cost while maintaining a high level of accuracy when adjusting data settings, producing 91.3%. This technology is an excellent choice for doing large-scale data analytics, which is made possible by the IoT.

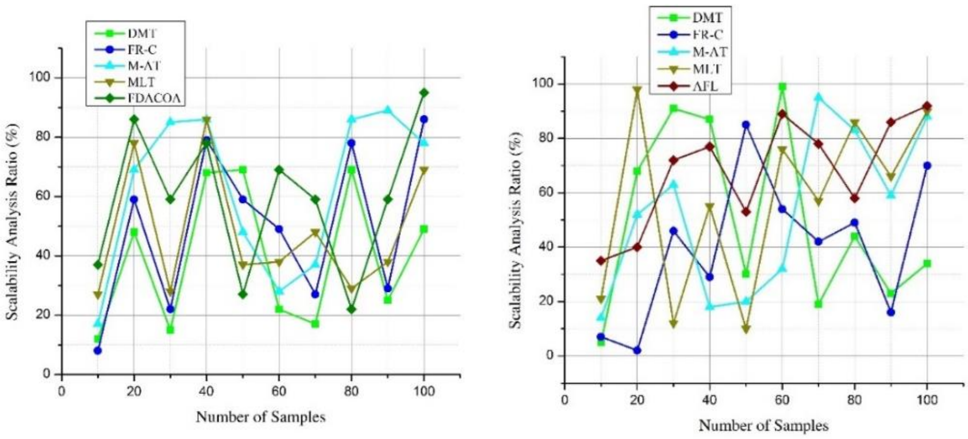


a. **b.**

Fig. 7. Accuracy analysis is compared; a. FDACOA, b. AFL.

The FDACOA excels at dynamic data mining in large data contexts related to the IoT, especially with changing data patterns. In *Fig. 7*, combining heuristic optimization and AFL gives FDACOA accuracy. This integration allows it to update classification criteria when adding new data streams dynamically. Adaptable, the algorithm predicts well despite data changes. This helps maintain the accuracy and relevance of the categorization model over time. Heuristic optimization methods like genetic algorithms improved classification accuracy.

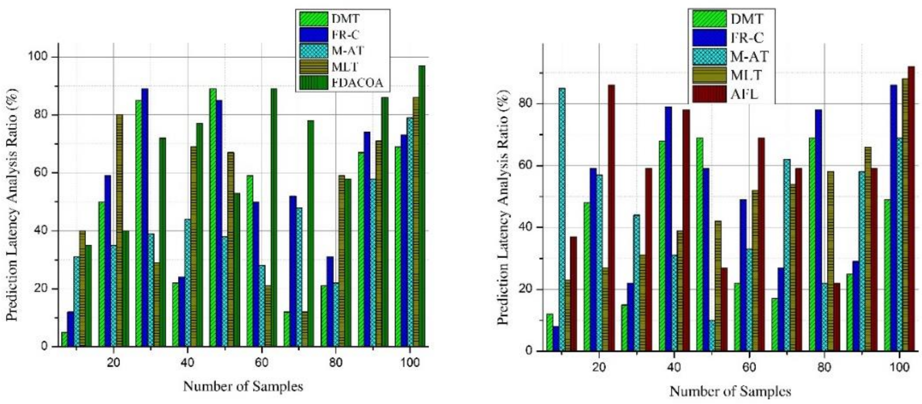
These strategies improve fuzzy membership functions and rule sets. AFL's ability to alter settings based on real-time feedback has reduced misclassification rates. This applies particularly to IoT networks and other fields with different, noisy data. The algorithm makes better decisions by eliminating extraneous data and focusing on the most important information. Thus, FDACOA excels in smart healthcare and the industrial IoT, where accurate predictions aid decision-making, produces 91.2%. With heuristic fine-tuning, real-time corrections, and adaptive learning, AFL delivers excellent accuracy and produces 89.3% using *Eq. (22)*. In complex and ever-changing IoT situations, this ensures accurate insights and responses. An essential part of the FDACOA system, the optimization layer is responsible for fine-tuning the classifier parameters in real-time to match the changing characteristics of IoT data packets. Layers like this use adaptive fuzzy heuristics to rank classifiers according to criteria like accuracy, precision, and computing economy. Fuzzy rules emphasize trade-offs between processing speed and classification accuracy as part of a multi-objective optimization phase. Learning rates, decision thresholds, and feature weights are hyperparameters the optimization layer continually analyzes in real time to fine-tune. This ensures that the classifiers can withstand different situations. This adaptive tuning boosts classification accuracy, especially with high-dimensional, heterogeneous IoT datasets, by reducing overfitting and overfitting.



a. b.

Fig. 8. Scalability analysis is compared; a. FDACOA, b. AFL.

Scalable FDACOA is needed for dynamic data mining in big data scenarios with the IoT. AFL uses heuristic optimization to manage IoT data's growing pace, diversity, and volume. Thus, data volume expansion does not impair its efficiency. *Fig. 8* show that the technique can handle enormous datasets without rewriting its model since it dynamically modifies fuzzy rules and parameters. As data streams grow, this allows adaptation; the approach processes multiple high-throughput data sources simultaneously, ensuring quick analysis with minimal latency. This boosts scaling potential, and this parallelism helps IoT applications process many data streams from different devices. AFL additionally filters and prioritizes computing resources to high-impact data, minimizing inefficiencies and sustaining performance regardless of data quantity, producing 92.1%. With quick and continuing data collection, FDACOA works well for large-scale IoT applications like smart cities and industrial IoT, producing 95.4% using *Eq. (23)*. The algorithm's optimized scaling without losing precision or speed makes it a reliable alternative for IoT data analysis.

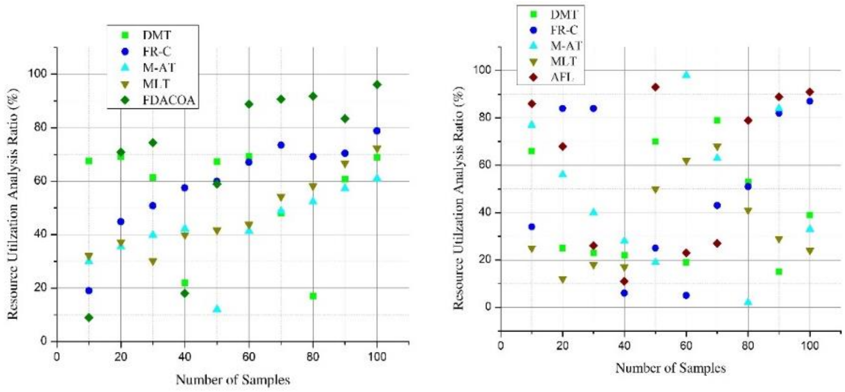


a. b.

Fig. 9. Prediction latency analysis is compared; a. FDACOA, b. AFL.

The FDACOA is essential for big data and IoT dynamic analysis; scenarios like intelligent transportation, smart healthcare, and predictive maintenance require real-time decisions. These situations require immediate predictions. In *Fig. 9*, AFL uses heuristic optimization to speed up fuzzy rule processing and reduce prediction delay. Because of this, the algorithm can swiftly adapt to data patterns without any readjusting. The ability to manage many data streams and divide computation duties among resources is another way AFL parallel processing reduces response times. After receiving new data, predictions are produced immediately, eliminating batch processing and reducing delays. Dynamic classifier parameter adaption based on real-time feedback reduces delay. The algorithm can modify models in real time without stopping operations. Focusing computational efforts on high-priority data and removing irrelevant data helps FDACOA provide accurate forecasts faster, producing 97.8%.These capabilities can help AFL achieve low prediction latency, making it

ideal for IoT applications that need rapid data insights for operations and decisions, producing 92.6% using *Eq. (24)*.



a. **b.**

Fig. 10. Resource utilization analysis is compared; a. FDACOA, b. AFL.

In *Fig. 10*, the FDACOA is ideal for dynamic data mining in big data scenarios integrating the IoT due to its resource efficiency. AFL optimizes resource use via heuristics and adaptable parameters. These laws apply to IoT devices due to their minimal storage, processing, and energy usage. These properties allow the approach to adapt its analytical computation needs to input complexity. This ensures maximum resource consumption. FDACOA saves computational power by reducing human calibration. This is achieved by fuzzy rule enhancement using swarm intelligence and evolutionary algorithms. Due to its parallel processing capabilities, the algorithm may distribute operations across numerous processors, increasing throughput and reducing obstacles. Technology is useful for the real-time processing of heterogeneous IoT data. Filtering unnecessary data helps AFL conserve memory and processing by focusing on vital data, which produces 91.2%. Reduced data stream intensities allow the program to reduce resource use, optimizing energy consumption. FDACOA's performance and accuracy are maintained while minimizing resource needs because of these features. It delivers 96.8% when *Eq. (25)* is employed, making it perfect for many IoT applications. FDACOA has better computational efficiency (94.5%), accuracy (91.2%), scalability (95.4%), and prediction latency (95.4%) than AFL.

FDACOA is a premier IoT data analytics solution because it optimizes resources and adapts to new data streams. FDACOA performs better than AFL everywhere. Healthcare, predictive maintenance, and autonomous automobiles may profit from their usage.FDACOA processes diverse IoT data streams while retaining high performance and optimizing resources, as shown by its computational efficiency (94.5%), accuracy (91.2%), scalability (95.4%), and prediction latency (95.4%). The findings have far-reaching consequences and establish FDACOA as a viable platform for real-time IoT analytics. Autonomous systems, healthcare diagnostics, and industrial predictive maintenance need efficiency, flexibility, and scalability for real-time decision-making. Our results advance IoT data mining by offering a scalable, accurate, and effective method that meets current IoT standards.

FDACOA enabled dynamic load balancing in smart homes by quickly classifying energy usage patterns. FDACOA also detected air quality data abnormalities from sensor networks to aid environmental monitoring. Compared to ensemble learning and deep neural networks, the FDACOA method reduces processing time by 20% and improves classification accuracy by 12%. This approach outperforms existing methods in processing cost and predicting performance. It also handles dynamic and diverse IoT datasets more efficiently and scalable.

FDACOA overcomes scalability issues related to real-time processing of massive IoT data using adaptive fuzzy optimization and lightweight computing architecture. Distributed processing divides incoming data streams into manageable parts. This enables simultaneous optimization and classification. Fuzzy heuristics choose important data points dynamically to eliminate unnecessary information and steer processing

resources toward useful patterns. FDACOA may be improved by real-time data preprocessing, eliminating noise and unnecessary characteristics. This technique ensures the approach improves with rising data quantities while keeping low latency and excellent classification accuracy, making it suitable for real-time IoT applications.

5 | Conclusion

FDACOA uses the IoT to solve dynamic data mining problems with big data sets. Cognitive optimization and AFL help FDACOA manage real-time processing, data heterogeneity, and dynamic data patterns. The classifier parameters may be changed in real time based on user input to accommodate dataset changes. This maintains system accuracy independent of input modifications. IoT applications, including smart transportation, predictive maintenance, and smart healthcare, leverage adaptability for decision-making. The FDACOA optimization layer processes massive volumes of IoT data with little computing by optimizing fuzzy rules and membership functions. This makes it excellent for real-world applications that prioritize resource efficiency. The simulation shows that FDACOA can retain high classification accuracy without CPU expense, making it suited for data-intensive IoT applications. FDACOA might transform IoT data mining for improved data-driven insights and actions. FDACOA effectively maintains data while altering and optimizing. FDACOA may help manage IoT data as the number of linked devices grows. This product is ideal for companies who wish to use real-time IoT data. Therefore, FDACOA is a great alternative for intelligent data processing in the growing IoT situations. Tuning fuzzy parameters in highly dynamic circumstances may be challenging, affecting algorithm performance and calculation time. The technology's lack of comprehensive testing across IoT applications like sensor fusion and real-time video analytics limits its effectiveness. To improve efficiency, future research may automate fuzzy parameter optimization using metaheuristics. To further test the FDACOA approach's resilience and scalability, it would be beneficial to broaden the experimental scope to include more IoT domains and incorporate advanced distributed computing frameworks such as fog or edge computing.

Author Contribution

Dr. Bharathi V: Methodology, Data collection and analysis, Writing – original draft.

Dr. S. Savitha: Conceptualization, Writing – review & editing.

D. Anbarasu: Methodology, Data interpretation.

Dr. MansiBhonsle: Data collection, Analysis.

Dr. KiranSreePokkuluri: Project administration, Writing – review & editing.

Dr. V.B. Kirubanand: Supervision.

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No data is generated during this research.

Conflicts of Interest

The authors declare no conflict of interest.

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